

# A Partition Approach to Model-based Diagnosis With Signal Information

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**Abstract**—This paper investigates farther the decomposition of diagnosis problem. Firstly, the relationship of test, component and signal attribute is described, the fault space of system is separated by the free-fault space, which can prune the diagnosis space, and minimal diagnosis was characterized by using function information. Secondly, this paper presents an algorithm for computing minimal diagnosis by using function information and an idea for partitioning the system by using function information. Finally, the correctness and completeness of the algorithm is proved, and the time complexity of the algorithm is also analyzed, which farther improves the effectiveness of diagnosing the systems and extends adaptability of decomposition of diagnosis problem

**Keywords**—model-based, diagnosis, test, system partition, Signal Information

## I. INTRODUCTION

Model-based diagnosis developed in recent years is a very active research branch in artificial intelligence, which motivation is to overcome the first-generation diagnostic expert system for defects. According to model-based diagnosis theory, the diagnosis model of the system and its expected behavior have been established, if the observed behavior of the system does not match the expected system behavior, all possible candidates diagnosis can be logically derived from the established system model. Since in many cases, there is much more one single failure or multiple failures, much more tests are applying to identify the real failure, which is the diagnostic test theory. In the past ten years, model-based diagnosis has been in-depth research, made a number of novel and meaningful ideas and methods were presented, but the study of diagnostic tests theory is less. The diagnostic test has been carried out in theory, which is described by some researchers, for example, in 1992, test of reasoning assumptions were characterized by McIlraith and Reiter; in 1994, diagnostic tests were characterized from the abduction perspective by McIlraith; in 1994 according to the Reiter's work, diagnostic measure were characterized from the

first principles by the Hou Aimin of China's scholars. In this paper functional attributes (i.e., function signal) is used to partition diagnostic system. Firstly, the relationship of test, component and signal attribute is described, the fault space of system is separated by the free-fault space, which can prune the diagnosis space, and minimal diagnosis was characterized by using function information. Secondly, this paper presents an algorithm for computing minimal diagnosis by using function information and an idea for partitioning the system by using function information. Finally, the correctness and completeness of the algorithm is proved, and the time complexity of the algorithm is also analysed.

## II. DESCRIPTION OF RELEVANT ISSUES

In order to facilitate understanding, here briefly introduce related concepts.

### A. Definition of related concepts

**Definition 1:** The system is a triple (SD, COMPS, OBS), where: SD is a collection of first-order sentences, denote the system description; COMPS is a finite set of constants denote system components; OBS is a set of first-order sentences, denote the system observation.

**Definition 2:** (SD, COMPS, OBS) is a system,  $(SD^{inf}, COMPS^{inf}, OBS^{inf})$  is its subsystems. Of which:  $SD^{inf}$  is a collection of first-order sentences, denote the subsystem description;  $COMPS^{inf}$  is a finite set of constants denote subsystem components;  $OBS^{inf}$  is a set of first-order sentences, denote the subsystem observation.

**Definition 3:** The system's signal flow graph, S is a system, G (V, E) is a signal flow diagram of the system, V is components or observed on behalf of, E is the signal between components or failure modes between the flow directions of propagation.

**Definition 4:** Related components: (SD, COMPS, OBS) is a system and  $OBS_i$  is the observation of a functional property, then a collection of components that contribute to the

functional properties of  $OBS_i$  is the related components of the functional attributes of  $OBS_i$ .

Diagnosis is based on the test, there is no diagnostic test, and diagnosis can not be implemented.

Definition 5: Test [9]: In order to confirm whether systems or components to meet the requirements, using manual or automated equipment to test or evaluation process. Test can be further divided into the automated testing and manual testing, external testing and machine testing. So the system (SD, COMPS, OBS) which increased testis expressed as  $(SD, COMPS, OBS \cup Test)$ . OBS is a special case of the test, the device can be understood as BIT.

For a test, this paper assumes that the test results are binary and symmetric.

Definition 6: A candidate diagnosis is assigned conjunct of each component of the system behavior, that is,

$\Delta \subseteq COMPS$ ,  $H = \{ab(c) | c \in \Delta\} \cup \{\neg ab(c) | c \in COMPS - \Delta\}$  is candidate diagnosis of (SD, COMPS, OBS), if and only if  $SD \cup OBS \cup H$  is satisfiable.

Definition 7: A candidate diagnosis of the subsystem is assigned conjunct of the behavior of functional attributes that is,  $\Delta^{inf} \subseteq COMPS^{inf}$ ,

$H^{inf} = \{ab(c^{inf}) | c^{inf} \in \Delta^{inf}\} \cup \{\neg ab(c^{inf}) | c^{inf} \in COMPS^{inf} - \Delta^{inf}\}$  is a candidate diagnosis of  $(SD^{inf}, COMPS^{inf}, OBS^{inf})$ , if and only if  $SD^{inf} \cup OBS^{inf} \cup H^{inf}$  is satisfiable.

Definition 8: Minimum Diagnosis: A diagnosis  $\Delta$  is minimal diagnosis, if there is not a diagnosis  $\Delta'$ , which make  $\Delta' \subset \Delta$ .

Definition 9: The combined set M of a collection of C is a collection of  $M \subseteq \bigcup_{S \in C, s \in S} S$ , which make  $S \in C$  existence and  $s \subseteq M$  satisfaction.

The combined set of M, such that for all the existence of, and satisfaction. Similarly, according to the definition of minimal diagnosis, define the minimum combination set.

Here we create the relationship between test, components (from the fault space, it is the fault) and signal attributes. Components COMPS represented  $f_i$  in the fault space.

Definition 10: in the fault space F is the fault set which need to detect and isolate, where  $f_i$  is one fault of the failure fault, and  $F \subseteq S$ , then the value of  $f_i$  is  $\{\text{the present, absent}\}$ .

Definition 11: T is test set used for fault detection, where  $t_i \in T$  a test of test set, which value is  $\{\text{Pass, Fail}\}$ .

Given test set T and systems S, and possible failure set F, we can determine whether the system malfunctioned. For any  $f_i \in F$ , we want to know whether  $val(f_i) = \text{present}$ . Because some tests can detect the fault appears, therefore, we can test the results of tests to determine whether the system malfunctioned. In other words: fault occurs or not we can determine by the value of the test.

Definition 12: D is the diagnosis signal set,  $D_i \in D$  is a collection of ordered pairs  $(t_i, v_i) \in T \times V$ , where,  $|D_i| = |T_i|$ ,  $v_i \in V$  and  $v_i \in \{\text{Pass, Fail}\}$ .

For a given fault a signal, our aim is to map each signal to the fault, or failure reflected the failed component.

Definition 13: diagnosis  $\Delta$  is a one to one mapping, namely,  $\Delta: D \leftrightarrow F$  (such as:  $\Delta: D \rightarrow F$ , or  $\Delta^{-1}: F \rightarrow D$ ).

Definition 14: the observations relationship exists between testing and fault: if and only if: a),  $val(f_j) = \text{present}$  then  $val(t_i) = \text{Fail}$ ; b),  $val(t_i) = \text{Pass}$ , then  $val(f_j) = \text{absent}$ .

Definition 15: the observation relationship between test  $t_i$  and test  $t_j$  exists: if and only if:

a),  $val(t_j) = \text{Fail}$ , then  $val(t_i) = \text{Fail}$ ;

b),  $val(t_i) = \text{Pass}$ , then  $val(t_j) = \text{Pass}$ .

If a test failed, the logic value of this test is true, if the test passed, the logic value is false.

Lemma 1: Let  $U = \{f_i | val(f_i) = \text{True}\}$ , if  $t_i \in T$ , and  $U \subseteq \{f_i | t_i \text{ test } f_i\}$ , then  $val(t_i) = \text{True}$ .

This lemma shows that if the test  $t_i$  can test the candidate fault set U, then  $t_i \in \{\text{Pass, Fail}\}$ .

Lemma 2: Given  $t_i \in T$ , Let  $\xi = \{f_j | t_i \text{ can test } f_j\}$ , if  $|\xi| > 0$ ,  $val(f_j) = \text{False}$ , and  $\forall f_j \in \xi$ , then  $val(t_i) = \text{False}$ .

This lemma shows that if the fault which can be detected by the test  $t_i$  is present, then  $val(t_i) = \text{Pass}$ .

## B. Correspondence between signal model and diagnosis

The correspondence between signal model and the propositional calculus of model-based diagnosis as follows:

Observation 1: The observed relationship is equivalent to the implication in the propositional calculus. So you can use *Pass/Fail* symbols to construct the truth table shown as TABLE I.

TABLE I  
TRUTH TABLE

$t_i$	$f_j$	$t_i \delta f_j$
Pass	Present	not hold (by definition)
Pass	Absent	hold (by definition)
Fail	Present	hold (by definition)
Fail	Absent	hold (by the information flow)

True assigned table can be formed as TABLE II.

TABLE III  
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$t_i$	$f_j$	$t_i \delta f_j$
False	True	False
False	False	True
True	True	True
True	False	True

This is clearly equivalent to truth table of  $f_j \rightarrow t_i$ .

Observation 2: The implication of these relationships is similar to the implication, so all the inference rules of the implication are hold (Inference, refused to take reasoning, transitive).

### III. DIAGNOSTIC ALGORITHMS FOR USING THE INFORMATION FLOW

#### A. Theorem about the Diagnostic Algorithms

Theorem 1: Let  $(SD, COMPS, OBS)$  is a system,

$COMPS^{inf} \subseteq COMPS$  is the related components of sub-functional attributes, if this sub-functional properties can describe the function, then the system are the system which can be divided into sub-system, and this diagnostic problem is decomposition.

From the perspective of the component functions and functional properties of sub-system, theorem 1 can be proved.

From theorem 1, using the parameters have been observed values and signal flow, we can decompose the whole system diagnostics to diagnose problems for each subsystem, which can reduce the complexity of diagnosing the problem.

Theorem 2: Using the signal property divide diagnostic system is complete.

From the system engineering point of view, the theorem can be proved.

Theorem 3: the candidate diagnosis of the system is the merge set of the candidate diagnosis of the sub-system, but the merge set can not the minimum diagnosis.

From the combined set and the definition of minimal diagnosis, the theorem can be proved.

#### B. Description of Diagnostic Algorithms

Algorithm 1: the diagnostic solutions by using the signal property

$COMPS$  is a finite set of system components,

$x_i \in COMPS, i = 1, 2, \dots, n$ ;

$COMPS^{inf}$  is a finite set of constants denote subsystem components,  $inf_m \subset inf, 1 \leq m \leq n$ ;

$num(COMPS^{inf})$  is the number of shared components of two subsystem,  $num(COMPS^{inf}) \leq m - 1$ ;

$num(inf)$  is the number of system,

System partition( )

```
{
   $COMPS^{inf_j} = \emptyset$ ;
  If (  $COMPS \neq \emptyset$  ) then
    If (  $x_i$  affect  $inf_j$  ) then
       $COMPS^{inf_j} = COMPS^{inf_j} \cup x_i$ ;
    Return  $COMPS^{inf_j}$ ;
  Else return  $COMPS^{inf_j}$ ;
  Else return  $\emptyset$ ;
}
```

Sub-diag( )

```
{
  If (  $val(OBS_j \delta COMPS^{inf_j}) = true$  and  $val(OBS_j) = true$  )
  then
     $\Delta_j = COMPS^{inf_j}$ ;
    If (  $val(t_i \delta OBS_j) = true$  ) then
      If (  $val(t_i \delta x_i) = true$  and  $val(t_i) = false$  ) then
         $\Delta_j = COMPS^{inf_j} - x_i$ ;
      Else
         $\Delta_j = COMPS^{inf_j}$ ;
      Else
         $\Delta_j = COMPS^{inf_j}$ ;
    Else return  $\emptyset$ ;
  }
  Merge( )
  {
    If (  $COMPS^{inf_i} \cap COMPS^{inf_j} = \emptyset$  ) then
       $\Delta = \bigcup_{1 \leq j \leq m} \Delta_j$ ;
    Else
       $COMPS^{com} = COMPS^i \cap COMPS^j$ ;
       $\Delta^{mer} = \Delta_i \cup \Delta_j$ ;
      For(j=1; j < num( $COMPS^{inf}$ ); j++)
        If (  $x_k \in COMPS^{com}$  ) then
          If (  $val((x_k \in COMPS^{inf_i}) \delta t_i) = true$  and  $val(t_i) = false$ 
and  $val((x_j \in COMPS^{inf_j}) \delta t_i) = true$  and  $val(t_j) = true$  ) then
             $\Delta^{mer} = \Delta^{mer} - x_k$ ;
          Else  $\Delta^{mer} = \Delta_i \cup \Delta_j$ ;
          Else  $\Delta^{mer} = \Delta_i \cup \Delta_j$ ;
        }
    main( )
    { if (System is small enough)
      Direct solution;
    Else
      System is divided into k sub-systems; ( System
partition( ); )
      For (i=1; i < num(inf); i++)
        Yi=Sub-diag( );
      Return merge(y1,y2,...,yk);
    }
```

Using this algorithm, the system function and various signal properties can be analysed firstly, according to the signal properties, the whole system can be divided into subsystems which can be affected by the each signal properties,

so, for the diagnosis of the subsystem, the candidate diagnosis is relative component associated with the signal attributes, the number of the subsystem compared with the entire system components decrease exponentially, therefore

the candidate diagnosis is only several, so the diagnosis efficiency can be improved, even in the worst case (The system can not be divided into sub-intersection), also diagnostic efficiency is better than in general, because the signal flow of information covers the structure.

### C. The completeness of the Diagnostic Algorithms

Theorem 4: Algorithm 1 is complete.

Proof: Algorithm 1 is divided into 4 steps to get, which is the system partition, sub-system diagnosis, merge of sub-system diagnosis and systems minimal diagnosis. Theorem 1 shows that partitioning the system with the signal properties is complete, minimal diagnosis of the sub-system is obtained through the sequence diagnosis, this process is complete, it need only demonstrate that merge of sub-system diagnosis is complete. From the subroutine Merge ( ), if there is no shared components between subsystems, merge of sub-system diagnosis is the system diagnosis, if the subsystem is shared between the components, you need to prune diagnose merge set. Pruning of merge set can be achieved by the relationship between the test and components and signals transitive, and the entire system diagnostic space is shrinking, so the merger of sub-system is complete, therefore algorithm 1 is complete. Proposition is proved.

### IV. CONCLUSION

This paper has done farther research on the decomposition of diagnosis problem. the idea of partitioning the system component by functional information of the system has present, and minimal diagnostic algorithm has present, the method is correct and complete, which further improve the diagnostic efficiency and expand the scope of diagnostic decomposition. These results not only apply to decomposition of non-hierarchical structure system and tree structure system, but also to the system with the electronic control unit has higher efficiency.

The improvement of the diagnosis efficiency depends largely on the test selection. The study of test selection is one of future research for model-based diagnosis.

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